Prediction of gait events in walking activities with a Bayesian perception system

Uriel Martinez-Hernandez, Mohammed I. Awad, Imran Mahmood and Abbas A. Dehghani-Sanij

***Abstract*— In this paper, a robust probabilistic formulation for prediction of gait events from human walking activities using wearable sensors is presented. This approach combines the output from a Bayesian perception system with observations from actions and decisions made over time. The perception system makes decisions about the current gait events, while observations from decisions and actions allow to predict the most probable gait event during walking activities. Furthermore, our proposed method is capable to evaluate the accuracy of its predictions, which permits to obtain a better performance and trade-off between accuracy and speed. In our work, we use data from wearable inertial measurement sensors attached to the thigh, shank and foot of human participants. The proposed perception system is validated with multiple experiments for recognition and prediction of gait events using angular velocity data from three walking activities; level-ground, ramp ascent and ramp descent. The results show that our method is fast, accurate and capable to evaluate and adapt its own performance. Overall, our Bayesian perception system demonstrates to be a suitable high-level method for the development of reliable and intelligent assistive and rehabilitation robots.**

I. INTRODUCTION

Recognition of activities of daily living (ADL) is a key task for the development of autonomous and rehabilitation robots capable to understand human motion and provide appropriate assistance [1], [2]. Particularly, walking across multiple terrains, ramp ascent and ramp descent are essential activities that provide humans with independence for living [3], [4]. However, these activities require coordinated movements that become difficult to execute by elder people or after suffering a physical injury [5].

Advanced sensors and sophisticated computational methods are required to achieve robust and reliable systems for human motion analysis. In recent years, large progress has been observed in wearable sensor technology –for instance, lightweight inertial measurement units (IMUs), soft kinematic sensors and multimodal interfaces [6], [7], [8], [9]. In contrast, slow progress has been observed in the deployment of fast and accurate computational methods for human motion analysis, recognition of walking activities and prediction of gait events [10], [11], [12]. Probably, this behaviour is related to the dependency on technology, which has made the design of computational methods a research line still under development.

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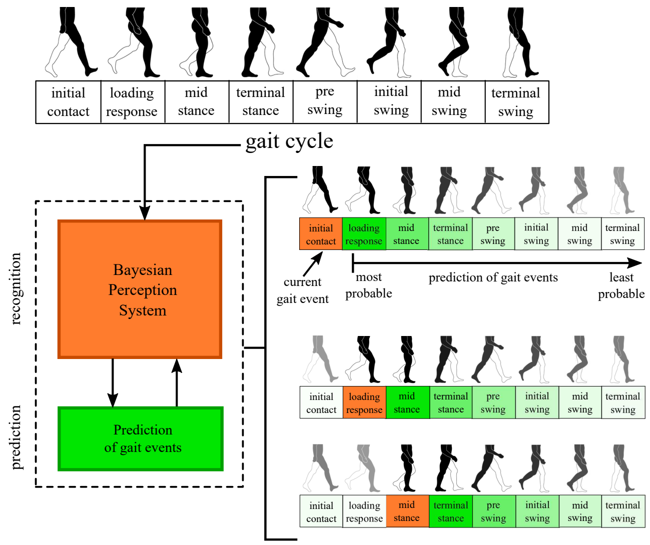

Fig. 1. Bayesian perception system for recognition and prediction of gait events. The gait cycle is divided into eight gait events. Our method performs two tasks; recognition of the current gait event (orange colour areas) and prediction of next gait events (green colour areas). The prediction module shows what is the next most and least probable gait event, represented by dark green and light green colours respectively.

In this work, we present a novel method for prediction of gait events which extends our previous work for recognition of walking activities [13]. First, our method for recognition of walking activities uses a Bayesian formulation that has demonstrated to be robust with different applications [14], [15], [16], [17]. Second, our method for prediction of gait events uses an approach based on the observation of decisions and actions made over time [18], [19]. Our method is motivated by the way in that humans make predictions or expectations according to the information and changes observed from their surrounding environment [20], [21]. The use of both recognition and prediction results (Figure 1), allows our approach to evaluate the accuracy of its predictions in order to adapt and achieve a better performance in accuracy and speed. These features make our perception system adaptable and reliable to uncertainty from sensor measurements and changes from the environment.

Our methods are implemented in a layered architecture composed of physical, perception and prediction layers. This type of architectures have shown to be a better approach for the development of modular, autonomous and scalable robotic systems [22], [23]. We use this architecture to validate the performance of our method with experiments for recognition and prediction of eight gait events (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing, terminal swing) from multiple walking activities. For these experiments we employed data collected from multiple human participants wearing three inertial measurement unit sensors, attached to their lower limbs and performing three different walking activities. Results from our experiments demonstrate the capability of our perception system to both, recognise and predict gait events with high accuracy and small decision time from ADLs.

Overall, our probabilistic method for prediction of gait events demonstrated to be robust, accurate and fast, which makes it suitable to develop wearable robots that autonomously provide safe and reliable assistance to humans in their activities of daily living.

intertial measurement unit pressure sensor

(A) Wearable sensors used for systematic data collection

(B) Level-ground walking

(C) Ramp ascent/descent

Fig. 2. Human participant performing multiple walking activities using wearable sensors for data collection. (A) IMU and pressure sensors used for systematic data collections. (B) Level-ground walking on a flat cement surface. (C) Ramp ascent and descent on a metallic ramp with a slope of 8.5 deg. Participant was asked to repeat ten times each walking activity.

II. METHODS

A. Experimental protocol and data collection

For our investigation we used angular velocity data from multiple IMU sensors worn by 12 healthy human participants. Anthropometric data from participants are as follows: ages between 24 and 34 years old, heights between 1.70 m and 1.82 m, and weights between 75.5 kg and 88 kg.

Data from IMU sensors were systematically collected from each participant to train and test our proposed method. For this process we employed three IMUs (Shimmer Inc.) attached to the thigh, shank and foot of participants. The signals received from sensors were sent to a workstation to be processed and analysed. We also used two foot pressure insoles sensors to detect the beginning and end of each gait cycle. A sampling rate of 100 Hz was used for data collection from these sensors attached to the human body. Both wearable devices, IMU and foot pressure sensors, provide a lightweight and low cost platform for the investigation and development of human-robot interaction, assistive and rehabilitation robotic systems [24], [25]. Figure 2A shows the sensors used for systematic data collection.

Participants were asked to walk normally at their self-selected walking speed while wearing IMUs attached to their lower limbs and foot pressure insole sensors. The participants performed ten repetitions of three different walking activities; level-ground walking, ramp ascent and ramp descent. Level-ground walking was performed on a flat cement surface (see Figure 2B). Both ramp ascent and descent were performed on a metallic ramp with a slope of 8.5 deg (see Figure 2C). The signals collected from walking activities were processed by a second-order Butterworth filter with a cut-off frequency of 10 Hz, prepared and stored in an appropriate format for their analysis with our approach for prediction of gait events. Figure 3 shows the angular velocities measured from the thigh, shank and foot for level-ground walking (black colour curves), ramp ascent (blue colour curves) and ramp descent (green colour curves). Solid and dashed lines represent mean angular velocities and standard deviations respectively. We divided the gait cycle for each walking activity into stance and swing phases, and eight events (initial contact, loading response, mid stance, terminal stance, pre-swing, initial swing, mid swing, terminal swing) as shown in Figure 4. This segmentation of the gait cycle, together with our Bayesian approach presented in Section II-B, allows us to determine and predict the state of the human body at specific moment for a certain walking activity.

B. Bayesian perception system

In this work we have extended our method for recognition of walking activities presented previously in [13] with a set of modules for prediction of gait phases and events during walking activities. The core of our proposed approach uses a Bayesian formulation that, based on the iterative accumulation of evidence from wearable sensors attached to the human lower limbs, allows to accurately recognise multiple human walking activities.

1) Bayesian formulation: the core of our recognition method uses a probabilistic formulation that recursively updates the posterior probability from the product of the prior probabilities and likelihood estimated over time. Here, we use the following notation:

- C is a finite set of classes or events $N = |C|$, e.g., here it denotes a set of the gait events.
- z represents the measurements from the wearable sensors attached to the human body.
- n denotes a specific gait event from the set N.

Then, the Bayesian formulation for recognition of gait events is performed as follows:

$$P(c_n|z_t) = \frac{P(z_t|c_n)P(c_n|z_{t-1})}{P(z_t|z_{t-1})} \quad (1)$$

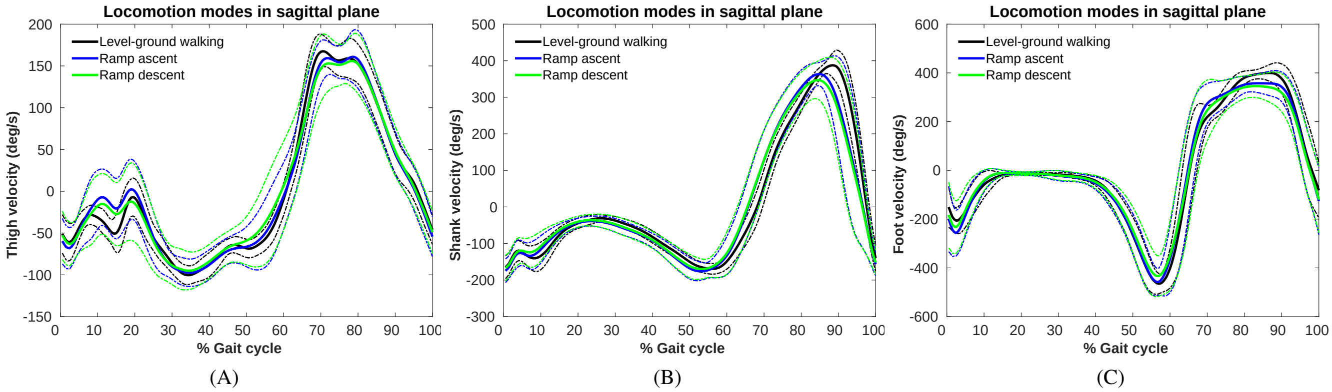

Fig. 3. Angular velocity data collected from three locomotion modes; level-ground walking, ramp ascent and ramp descent represented by black, blue and green colour curves. The data were collected using three inertial measurement units (IMUs) attached to (A) the thigh, (B) shank and (C) foot of healthy human participants. Solid lines show the mean angular velocities for each locomotion mode, while dashed-lines represent the standard deviation.

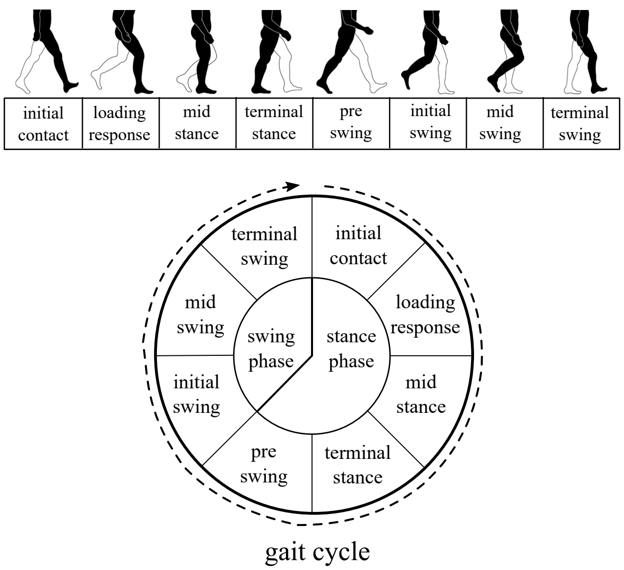

Fig. 4. Diagram that depicts the gait phases and segmentation of the gait cycle into eight gait events: (1) initial contact, (2) loading phase, (3) mid stance, (4) terminal stance, (5) pre-swing, (6) initial swing, (7) mid swing, (8) terminal swing. This information is used by our perception system to perform the recognition and prediction of gait events. Also, this process allows to know when the gait cycle is in stance and swing phase.

where $P(c_n|z_t)$ is the posterior probability of a gait event c_n given the sensor measurements z_t at time t, and $P(z_t|c_n)$ is the likelihood of the sensor measurements z_t given the gait event c_n at time t. The prior probability represented by $P(c_n|z_{t-1})$ for time $t > 0$ is updated with the posterior probability estimated at time $t-1$. Here, $n = 1, 2, \ldots, N$ with $N = 8$ gait events (see gait events in Figure 4). The posterior in Equation 1 is iteratively updated and a decision about the gait event is made once a predefined belief threshold $\beta_{\text{threshold}}$ is exceeded. The decision-making process to recognise a gait event is performed as follows:

$$\begin{gathered}\text{if any } P(c_n|z_t) > \beta_{\text{threshold}} \text{ then} \\ \hat{c} = \arg\max_{c_n} P(c_n|z_t)\end{gathered} \tag{2}$$

where the estimated gait event $\hat{c}$ at time t is obtained using the *maximum a posteriori* (MAP) estimate. We can control the confidence of our Bayesian perception system by adjusting the belief threshold $\beta_{\text{threshold}}$, which allows to control the desired accuracy for the recognition process. The physical and perception layers in Figure 5 contain the processes for sensor data collection and Bayesian perception. For more details about the estimation of the parameters of our Bayesian perception system and their application for different tasks see [13], [26].

Our Bayesian formulation method assumes an initial uniform prior probability distribution for each new decision-making process. However, humans normally make decisions using the knowledge and observations learned from previous events, which generate non-uniform initial priors. This aspect contributes to attain accurate and fast decisions, but also to predict next events based on the observation of past decisions and actions. For that reason, we have extended our Bayesian formulation with a prediction layer based on the observation and evaluation of past decisions and actions.

C. Prediction of gait events

For prediction of gait events we obtain a predicted probability distribution, which is estimated by the observation of transitions between gait events (eight events, see Figure 4) over time. The predicted probability is obtained as follows:

$$P_{\text{predicted}}(c_n|z_\tau) = P(c_n|z_{\tau-1}) + \Delta \tag{3}$$

where $P_{\text{predicted}}(c_n|z_\tau)$ is the predicted probability distribution used for initialisation of the new decision-making process at time τ. $P(c_n|z_{\tau-1})$ is the posterior distribution from previous decisions made by our Bayesian formulation. The parameter Δ is learned by the observation of how transitions between gait events occur from previous $\hat{c}_{\tau-1}$ and current $\hat{c}_\tau$ decisions made over time τ as follows:

$$\Delta = \hat{c}_\tau - \hat{c}_{\tau-1} \tag{4}$$

where $\Delta \in \{0, \ldots, 7\}$ estimates the transition between gait events to obtain the predicted probability distribution for next decision-making process during the walking cycle. We use the MAP estimate to obtain the most probable predicted class $\tilde{c}_\tau$ from $P_{\text{predicted}}(c_n|z_\tau)$ as follows:

$$\tilde{c_\tau} = \arg\max_{c_n} P_{\text{predicted}}(c_n|z_\tau) \tag{5}$$

In order to ensure reliable predictions and decisions made by our approach, we evaluate the accuracy of the predicted class or gait event. The evaluation process is as follows:

$$\xi_\tau = (\beta_{\text{threshold}} - (\hat{c}_\tau - \tilde{c}_{\tau-1})) \tag{6}$$

where ξ_τ is the accuracy of the predicted gait event estimated at previous time. Equation 6 is used to determine whether our recognition system needs to rely or give more weight to predictions or current observations to ensure the best performance. Then, we use the parameter ξ_τ to obtain the weighting parameter α at decision time τ as follows:

$$\alpha_\tau = \left(\frac{\tau-1}{\tau}\right)\alpha_{\tau-1} + \left(\frac{1}{\tau}\right)\xi_\tau \tag{7}$$

$$P(c_n|z_\tau) = \alpha_\tau P_{\text{predicted}}(c_n|z_\tau) + (1-\alpha_\tau)P_{\text{flat}}(c_n) \tag{8}$$

where $P(c_n|z_\tau)$ is the prior distribution that initialises the new decision process τ. This prior distribution is obtained by the weighted combination of the predicted distribution and a uniform distribution $P_{\text{flat}}(c_n)$. Equation 8 shows that our probabilistic system autonomously uses more information from the data source that is more accurate. For example, our method relies more on $P_{\text{predicted}}$ when predictions are accurate, reducing the contribution from the uniform distribution and vice versa. Notice that when $\alpha = 0$ the predicted distribution does not contribute and our method behaves as the Bayesian formulation shown in Section II-B.

Figure 5 shows a high level description of our approach using a layered control architecture composed of physical, perception and prediction layers. The physical layer contains sensation and data preparation processes. Next, the perception layer processes and analyses the data by implementing our Bayesian formulation for perception. The output from our perception approach is used to predict the next gait events by the processes implemented in the prediction layer.

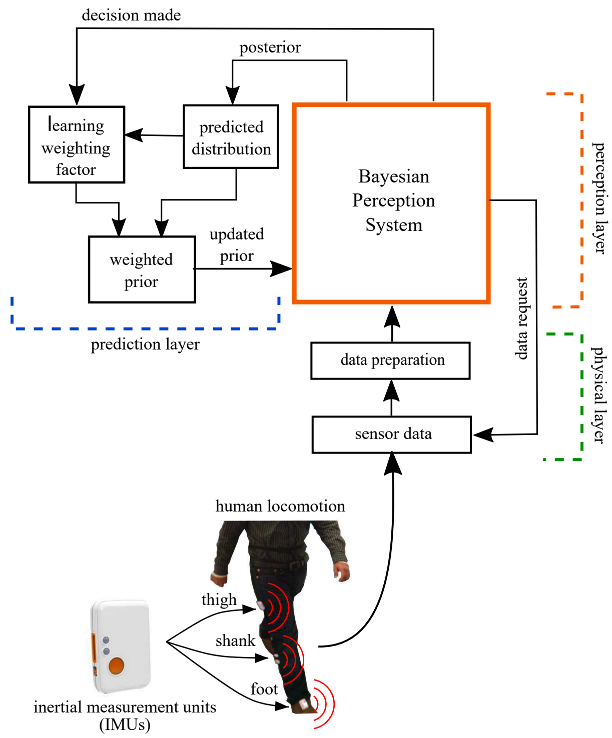

Fig. 5. Control architecture that implements our Bayesian perception system for recognition and prediction of gait events. This architecture is divided in physical, perception and prediction layers. The physical layer interacts directly with the environment, e.g., the human and wearable devices, and it is responsible for data collection. The data received from IMU sensors are prepared in the appropriate format for their analysis. The perception layer implements the Bayesian formulation, based on the combination of the prior probability and likelihood. Control of the amount of sensor data required to make a decision is also performed by the perception layer. The prediction layer implements our approach for prediction of gait events by adapting the prior probability based on the observation of decisions made over time.

III. RESULTS

The Bayesian perception system is validated in both accuracy and speed with experiments for recognition and prediction of gait events. In these experiments training and testing data sets are collected from IMU sensors attached to the lower limbs of human participants (see Section II-A).

A. Recognition of gait events

First, we validate the accuracy and speed of our perception system for recognition of gait events for different walking activities. For this experiment we use angular velocity signals from level-ground walking, ramp ascent and ramp descent. These signals measured from the thigh, shank and foot of human participants are shown in Figure 3. The eight segments in which the gait cycle is divided for recognition of gait events are shown in Figure 4. All data collected from all participants are prepared and grouped into training and testing data sets for validation of our proposed method.

Our Bayesian perception system is configured with C ={initial contact, loading phase, mid stance, terminal stance, pre-swing, initial swing, mid swing, terminal swing} and $N = 8$ that represent the gait events. We also defined $\beta_{\text{threshold}} = [0.0, 0.05, \ldots, 0.99]$ to evaluate the recognition accuracy and decision time for different levels of confidence employed by our proposed perception method. In this experiment for recognition accuracy and speed our method randomly draws samples from the testing data set. This process was repeated 10,000 iterations for each belief threshold value in $\beta_{\text{threshold}}$. Averaged results over all walking activities for recognition accuracy of gait events against belief threshold are shown in Figure 6A. We observe that the recognition accuracy for gait events is gradually improved from a mean error of 5% to a mean error of 0.13% with threshold values of $\beta_{\text{threshold}} = 0.0$ and $\beta_{\text{threshold}} = 0.99$ respectively. The plot of decision time against belief threshold in Figure 6B shows the speed of our method to make a decision. These

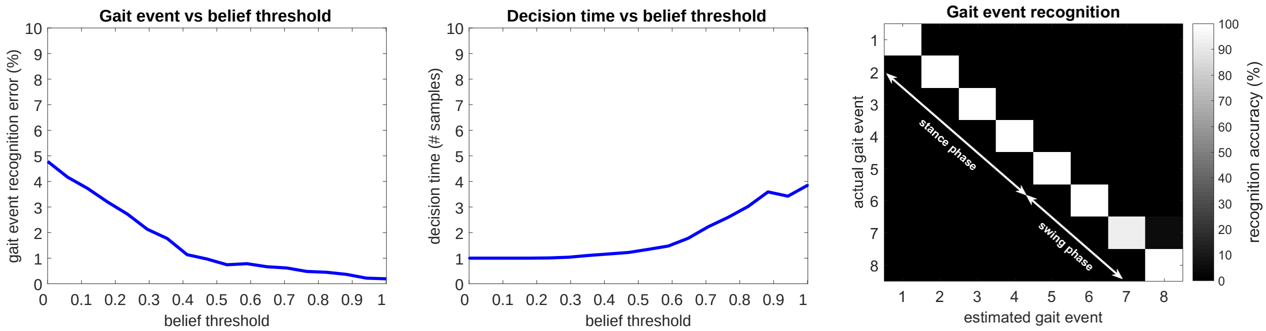

Fig. 6. Recognition of gait events with our Bayesian perception system. (A) Mean recognition error of gait events gradually decrease for large belief thresholds achieving the smallest error of 0.13%. (B) Increments in the confidence level of our perception system also shows a gradual increment in the mean time to make a decision, where 4 samples (40 ms) are required to achieve the highest gait event recognition accuracy. (C) Confusion matrix with accuracy recognition of each gait event and stance and swing phases.

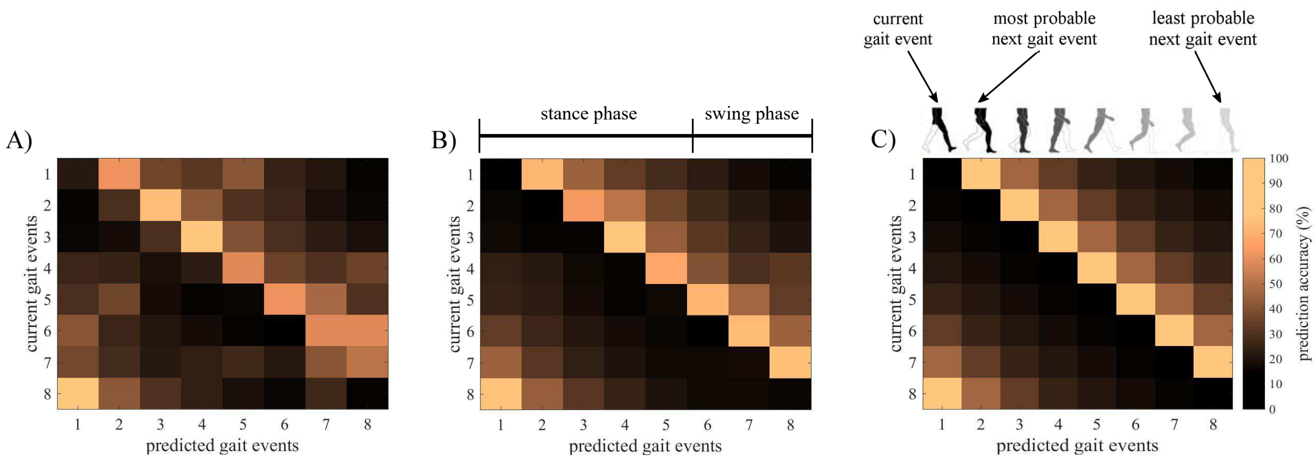

Fig. 7. Confusion matrices with prediction accuracy of the eight gait events that composed the gait cycle: (1) initial contact, (2) loading phase, (3) mid stance, (4) terminal stance, (5) pre-swing, (6) initial swing, (7) mid swing, (8) terminal swing. The accuracy for prediction of the most probable gait events, for three walking activities, are shown in black and light brown colours, which represent low and high probability respectively. (A) Very low accurate prediction results (x axis), which is related to the low belief threshold $\beta_{\text{threshold}} = 0$ and the low accurate recognition of the current gait event (y axis). (B) Both recognition and prediction of gait events are improved with a belief threshold of $\beta_{\text{threshold}} = 0.8$. (C) Highly accurate recognition and prediction of gait events achieved with a belief threshold $\beta_{\text{threshold}} = 0.99$.

decision times gradually increase from a mean of 1 to 4 sensor samples with $\beta_{\text{threshold}} = 0.0$ and $\beta_{\text{threshold}} = 0.99$ respectively. This shows that our perception system requires a mean of 40 ms (sampling rate of 100 Hz) to make a decision with the highest accuracy of 99.87%.

Recognition accuracy for each gait event is shown by the confusion matrix in Figure 6C, where black and white colours represent low and high accuracy respectively. We observe that the accuracy for recognition of each gait event is high, but also these results allow to determine in which gait phase is the human currently, e.g., stance or swing phase. This information from both, gait event and gait phase, provide a better knowledge about the current state of the walking activity, which can be used to develop more robust and intelligent devices that safely assist humans in ADLs.

B. Prediction of gait events

Prediction results of gait events for different belief threshold values $\beta_{\text{threshold}}$ and averaged over all walking activities are presented by confusion matrices in Figure 7. These results show the accuracy of our Bayesian perception system to predict the next most probable gait event based on the recognition of the current event and observation of previous decisions. Rows of each confusion matrix show the current recognised events, while columns show the most (light brown colour) and least (black colour) probable gait events. Figure 7A shows the confusion matrix obtained with $\beta_{\text{threshold}} = 0.0$, which achieved low accuracy for prediction of gait events. This result is related to the low accuracy for recognition of current gait events given the low value of the belief threshold. Figure 7B shows the results when the confidence of our perception system was increased to $\beta_{\text{threshold}} = 0.8$. In this confusion matrix we observe that the perception system is capable to achieve better predictions for next gait events, which also improves the accuracy to recognise whether the gait cycle is in stance or swing phase. The highest accuracy was achieved with $\beta_{\text{threshold}} = 0.99$ shown by the confusion matrix in Figure 7C. Here, again our Bayesian perception system was capable to both accurately recognise the current gait event and predict the most probable gait events. Interestingly, our perception system is able to achieve high recognition and prediction results with a mean of 4 sensor samples (40 ms) as shown by plot C in Figure 6. These results validate our proposed method that, adapting the prior distribution of our Bayesian perception system by learning the parameters Δ and α, improves the accuracy and speed for recognition and prediction of gait events. This predictive functionality offered by our perception method, at high-level layer, can be used to prepare low-level controllers to act according to the predicted or anticipated gait events for safe assistance to humans in their activities of daily living.

IV. CONCLUSIONS

In this work we presented a Bayesian perception system for prediction of gait events. This method extends our previous work for recognition of walking activities. For prediction of gait events we developed a method based on the observation of actions and decisions made by our Bayesian perception system over time. This observation allows to learn a transition parameter which is used to obtain a predicted probability distribution. Our perception system is also capable to evaluate its own performance, allowing to autonomously adjust the amount of information to be used from the predictions obtained over time. We validated our Bayesian perception system with the prediction of gait events for multiple walking activities. First, we collected angular velocity data from three IMU sensors attached to the lower limbs of human participants. The data collected were prepared for training and testing phases. Second, we divided the gait cycle into eight gait events. Third, we performed various experiments where we observed that our perception system is capable to achieve fast and high accuracy of both recognition and prediction of gait events.

Overall, our Bayesian perception systems demonstrated to be accurate and fast for recognition and prediction of human movements using wearable sensors. Furthermore, the features offered by our work, integrated together with low-level controllers, provide a reliable approach to develop intelligent robotic devices that safely assist humans in ADLs.

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